DOCUMENT RESUME

ED 393 913 TM 024 914

AUTHOR Donoghue, John R.
TITLE A Preliminary Comparison of the Effectiveness of Cluster Analysis Weighting Procedures for Within-Group Covariance Structure.
INSTITUTION Educational Testing Service, Princeton, N.J.
REPORT NO ETS-RR-95-35
PUB DATE Oct 95
NOTE 63p.; Version of a paper presented at the Annual Meeting of the American Educational Research Association (New Orleans, LA, April 4-8, 1994).
PUB TYPE Reports - Evaluative/Feasibility (142) -- Speeches/Conference Papers (150)

EDRS PRICE MF01/PC03 Plus Postage.
DESCRIPTORS Algorithms; *Cluster Analysis; Comparative Analysis; Correlation; Monte Carlo Methods; *Research Methodology; Simulation
IDENTIFIERS *Covariance Structure Models; *Weighting (Statistical)

ABSTRACT

A Monte Carlo study compared the usefulness of six variable weighting methods for cluster analysis. Data were 100 bivariate observations from 2 subgroups, generated according to a finite normal mixture model. Subgroup size, within-group correlation, within-group variance, and distance between subgroup centroids were manipulated. Of the clustering methods examined, the flexible average algorithm with beta equal to -.15 or -.20 gave the best recovery. Of the remaining methods, that of J. H. Ward yielded the best recovery, followed closely by beta-flexible linkage and the EML algorithm of the Statistical Analysis System. In the absence of variable weights, negative within-group correlation resulted in much poorer recovery for all clustering algorithms. The ACE weighing method of D. Art, R. Gnanadesikan, and J. R. Kettenring proved preferable overall. Clustering with Mahalanobis distance based on the pooled within-group covariance matrix indicated that knowing the correct covariance method would yield improved recovery over the ACE method approximately 10% of the time. Two appendix figures provide weighting data. (Contains 8 figures, 7 tables, 2 appendix figures, and 40 references.) (Author/SLD)

****
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
****

RR-95-35

ED 393 913

RESEARCH REPORT

U.S. DEPARTMENT OF EDUCATION
Office of Educational Research and Improvement
EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)

☑ This document has been reproduced as received from the person or organization originating it.

☐ Minor changes have been made to improve reproduction quality.

• Points of view or opinions stated in this document do not necessarily represent official OERI position or policy.

"PERMISSION TO REPRODUCE THIS MATERIAL HAS BEEN GRANTED BY

H. I. BRAUN

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

A PRELIMINARY COMPARISON OF THE EFFECTIVENESS OF CLUSTER ANALYSIS WEIGHTING PROCEDURES FOR WITHIN-GROUP COVARIANCE STRUCTURE

John R. Donoghue

Educational Testing Service
Princeton, New Jersey
October 1995

BEST COPY AVAILABLE

TM024914

A Preliminary Comparison of the Effectiveness of Cluster Analysis Weighting Procedures for Within-group Covariance Structure

John R. Donoghue

Educational Testing Service

This research was supported by Educational Testing Service Research Allocation Project 794-10. An earlier version of this paper presented at the Educational Statisticians SIG at the annual meeting of the American Educational Research Association in New Orleans, LA, April 1994. The author would like to thank Carolyn Crone and Scott Wesley for their helpful comments.

Copyright © 1995. Educational Testing Service. All rights reserved.

Abstract

A Monte Carlo study compared the usefulness of six variable weighting methods for cluster analysis. Datasets were 100 bivariate observations from two subgroups, generated according to a finite normal mixture model. Subgroup size, within-group correlation, within-group variance, and distance between subgroup centroids were manipulated.

Of the clustering methods examined, the flexible average clustering algorithm with β = -.15 or -.20 gave the best recovery. Of the remaining methods, Ward's method yielded the best recovery, followed closely by beta-flexible linkage (β = -.50) and SAS's EML algorithm.

In the absence of variable weights, negative within-group correlation resulted in much poorer recovery for all clustering algorithms. The ACE weighting method of Art, Gnanadesikan, and Kettenring provided a net improvement in 17-24% of the datasets when used with better clustering algorithms. When used with the same clustering alogrithms, De Soete's ultrametric weighting yielded improved recovery 16-22% of the time. However, although ultrametric weighting was more sensitive than ACE to negative within-subgroup correlation. Clustering based on principal components was less effective. Therefore, the ACE method is preferred overall.

There is still room for improvement, however. Clustering with Mahalanobis distance based on the pooled within-group covariance matrix indicated that knowing the correct covariance matrix would yield improved recovery (over ACE) approximately 10% of the time.

Often in educational and psychological research, a researcher is confronted by a population which, for lack of a better term, seems too heterogeneous. In such circumstances, the investigator is likely to hypothesize that the population under study is actually composed of two or more relatively homogeneous subgroups. For example, several investigators have suggested that the umbrella term "learning disabilities" actually encompasses a variety of disorders, with different etiologies and strategies for treatment.

In such circumstances, one may appeal to clinical insight to describe possible subgroups. However, to bolster such insight, the investigator may also turn to the statistical method of cluster analysis to try to isolate relatively homogeneous subgroups within the more heterogeneous population. Indeed, cluster analysis often has been used to try to identify putative subtypes of learning disability.

Unfortunately, the applied investigator is faced with a myriad of clustering techniques, most of which present options and suboptions in the analysis. To guide these choices, numerous studies have examined various aspects of the clustering process, including comparison of clustering algorithms (e.g., Belbin, Faith, & Milligan, 1992; Blashfield, 1976; Donoghue, 1994b, 1995; Milligan, 1979, 1989a; Scheibler & Schneider, 1985), the effect of various types of "error" in the data to be clustered (Milligan, 1980), variable standardization (Milligan & Cooper, 1988; Barton, 1993), selection/weighting of irrelevant variables (De Soete, 1986, 1988; Milligan, 1989b; Donoghue, 1994a), procedures to determine the number of clusters (e.g., Milligan & Cooper, 1985), and procedures to compare clustering solutions (Milligan & Cooper, 1986).

Although these studies have obtained a variety of useful findings, one aspect of the clustering process has not received much attention: the within-group covariance structure. Recent work (Donoghue, 1994b) examined the case of two groups in two dimensions, and found a very large effect of within-group correlation. Specifically, within-group correlation which did not coincide with the direction of separation

in subgroup means was associated with lower recovery for all clustering methods; within-group correlation which did coincide with the direction of separation was associated with higher recovery. This result was interpreted in terms of the similarity[1] measure used, the Euclidean distance.

A fundamental issue raised by Donoghue (1994b) is what the analyst should do to minimize the deleterious effect of within-group correlation. Donoghue suggested several possible alternatives to the Euclidean distance, but, in the absence of comparative data, could provide no guidance. The present study compares several of these variable weighting methods. In the remainder of this section, the finite mixture model which implicitly underlies this work will be introduced, and the various weighting strategies used in this study will be examined.

The Finite Mixture Model

This paper adopts the view of cluster analysis as the attempt to "unmix a mixture of distributions" (e.g., Titterington, Smith, & Makov, 1985; McLachlan & Basford, 1988). This finite mixture model states that the distribution function for the entire population, h(x), is given by:

$$h(x) = \sum_{g=1}^{G} \pi_g f_g(x) \quad , \qquad \pi_g > 0, \quad \sum_{g=1}^{G} \pi_g = 1 \quad . \tag{1}$$

Subgroups are the homogeneous distributions $f_g(x)$, which are mixed, and the π_g are termed the "mixing proportions." The conceptual framework of the finite mixture model of clustering underlies the present paper, and some of the results may not make sense in situations in which the finite mixture model does not apply.

---

[1] The general term "measure of similarity" will be used in this paper to denote both true measures of similarity, such as correlations and coefficients of concordance, and measures of *dis*similarity, such as distances.

In the discussion that follows, **X** will be the full (entities by variables) data vector, and $\mathbf{x}_i$ be the column vector of variable values associated with entity *i* (i.e, the transpose of the *i*th row of matrix **X**.

Variable Weighting Methods

Prior to clustering, hierarchical clustering methods convert two-mode (variables by entities) multivariate data into a one-mode (entities by entities) univariate measure of similarity, which is then used as the basis of the clustering. The vast majority of clustering studies (applied and simulation) use d_E, Euclidean distance (or the squared distance) between entities *i* and *j* as similarity measure:

$$d_E(ij) = \sqrt{\sum_{p=1}^{P} (x_{ip} - x_{jp})^2} \quad , \tag{2}$$

where P is the number of variables used in the clustering. Basic geometry of vector spaces reveals that Euclidean distance is correct only if computed on an orthogonal basis. If the variables are correlated, the Euclidean distance can misrepresent the distance between two points. By ignoring the within-group correlations of variables, Donoghue (1994b) demonstrated that d_E can seriously degrade cluster recovery.

Euclidean distance is widely used and is the default measure for most clustering software. However, most hierarchical clustering algorithms can make use of any one-mode measure, and other similarity measures are available. Two commonly mentioned possibilities are Mahalanobis distance D_M and clustering based upon principal component scores. The problems with these obvious choices will be discussed, and then some possible alternatives will be discussed.

Mahalanobis Distance

Ideally, one would cluster based on the Mahalanobis distance measure, D_M:

$$D_M(ij) = (\mathbf{x}_i - \mathbf{x}_j)' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \mathbf{x}_j) \quad . \tag{3}$$

In practice however, D_M is difficult to compute because of the difficulty in estimating the appropriate Σ matrix. The correct choice is the pooled within-group covariance matrix, Σ_W:

$$\Sigma_w = \sum_{g=1}^{G} \pi_g \Sigma_g \quad . \tag{4}$$

Without knowing the subgroup structure, it is not possible to compute the Σ_g matrices. An alternative is to use the overall covariance matrix, Σ_T:

$$\Sigma_T = \frac{1}{n}(X-\bar{X})'(X-\bar{X}) \quad . \tag{5}$$

However, the standard MANOVA decomposition reveals:

$$\Sigma_T = \Sigma_B + \Sigma_W \quad . \tag{6}$$

The inclusion of Σ_B can give Σ_T very different properties from Σ_W. Hartigan (1975, p. 63) provides an example demonstrating that D_M based on Σ_T can result in worse cluster recovery than using d_E.

Principal Components

Another commonly suggested alternative is to cluster based upon principal component scores rather than the original variables. The chief advantage of this method is that principal component scores are orthogonal to one another; because d_E implicitly assumes orthogonal variables, clustering based on the principal components seems to remove the objections to this measure. However, the difficulty with principal components is identical to that of D_M. The ideal is to perform principal components analysis based on Σ_W. In practice, however, Σ_W is not known, and so component scores are computed based on Σ_T (or the correlation matrix R_T). As is the case with D_M, the inclusion of Σ_B can give Σ_T very different properties from Σ_W. Rohlf (1970) discusses some of the difficulties with using principal components, and Chang (1983) gives a theoretical analysis of the difficulties involved, and provides a clear example of the

problems with this approach.

The ACE Algorithm

Art, Gnanadesikan, and Kettenring (1982) devised an ingenious method to estimate the pooled within-group covariance matrix without knowledge of the subgroup structure. They start with the known property that the covariance can be computed from inter-entity relations:

$$\sigma_{kl} = \frac{1}{2n} \sum_{i}^{n} \sum_{j}^{n} (x_{ik} - x_{jk})(x_{il} - x_{jl}) \quad . \tag{7}$$

Analogous to the usual MANOVA decomposition in Equation (7), the inter-entity relations give a between- and within-groups decomposition:

$$T = B^{*} + W^{*} \quad . \tag{8}$$

If Δ is the matrix of differences between subgroup centroids, Art Gnanadesikan, and Kettenring show that $W^{*-1}\Delta$ has the same eigenvectors as $W^{-1}\Delta$, and so D_M based on W^{*} is equivalent (up to a multiplicative constant) to D_M based on W.

Reasoning that most of the smaller inter-entity distances are likely to be within-group distances, Art Gnanadesikan, and Kettenring use the inter-entity relations from the *m* smallest distances to form an approximate covariance estimate (ACE), W^{*}:

$$W^{*} = \frac{1}{n} \sum_{d_{ij} \in m} (x_i - x_j)'(x_i - x_j) \tag{9}$$

where the summation runs over the *m* smallest pairs. The distances are then recomputed as D_M based on W^{*}, and the process repeated until the current estimate of W^{*} does not differ significantly from that of the previous iteration.

A modified version of ACE is computed by SAS's PROC ACECLUS (SAS Institute, 1988),

including the option to output a matrix of inter-entity similarities for further analysis. The present study used the original algorithm given in Art, Gnanadesikan, and Kettenring (1982). To date, I am not aware of any published studies (beyond the original article) of this approach, although work is underway at Bellcore (J. Kettenring, personal communication, July 2, 1993).

Ultrametric Weights

De Soete (1986, 1988) developed an algorithm which determines weights to apply to variables in computing a distance measure:

$$d_u(ij) = \sqrt{\sum_{p=1}^{P} w_p (x_{ip} - x_{jp})^2} \quad , \qquad w_p > 0, \ \sum_{p=1}^{P} w_p = 1 \quad . \tag{10}$$

The weights are chosen so that the resultant distances maximally satisfy the "ultrametric inequality," which states that any three points i, j, and k, the distances between the points should satisfy the relation:

$$d_{ij} \leq \max (d_{ik}, d_{jk}) \quad . \tag{11}$$

This is equivalent to requiring all sets of three points to lie on an acute isosceles (or equilateral) triangle. Johnson (1967) and Milligan (1979) demonstrated the relationship between the ultrametric inequality and many commonly used hierarchical clustering algorithms, and Milligan and Isaac (1980) give simulation results which provide support for the utility of the conceptualization. Two studies (Milligan, 1989b, Donoghue, 1994a) have examined De Soete's algorithm, and found that it greatly improved cluster recovery when the data contained "error" dimensions, i.e, dimensions which contained no information about subgroup membership. However, it is not known whether this method helps with the difficulties of within-group covariance structure.

The present study sought to examine these weighting strategies, and compare their usefulness in recovering known subgroup structure in data with the presence of a variety of within-group covariance structures.

Method

This study used Monte Carlo methods to systematically investigate the utility of various variable weighting methods to account for the effects within-group covariance structures. Subgroups were generated according to a model of a finite mixture of normal distributions (e.g., McLachlan & Basford, 1988). Similar to Donoghue (1994b), the study will examine the limited case of two groups in two dimensions, but this case will be examined in some detail. While restricting the investigation to bivariate data somewhat limits its generalizability, this provides a minimal test of the weighting procedures; any procedure which does not function well with bivariate data seems unlikely to be useful for higher dimensional cases.

Design

Five aspects of the data were manipulated in data generation. The first three of these determined the within-group covariance matrices.

1) R1: The within-group correlation of subgroup 1 (3 levels)-- $r_1 = -.7, 0.0, .7$.
2) R2: The within-group correlation of subgroup 2 (3 levels)-- $r_2 = -.7, 0.0, .7$.
3) COV: The relationship of the within-group covariance matrices (5 levels). For the first three levels, the variances of each variable were equal ($\sigma^2_{1_g} = \sigma^2_{2_g}$) within a subgroup, and both of the variances of the second subgroup were equal to a constant times the variance within the first subgroup ($\sigma^2_{12} = k\sigma^2_{11}$, $\sigma^2_{22} = k\sigma^2_{21}$). For the last two conditions, the variances of the two

variables within a subgroup differed. The within-subgroup matrices were equal for one of the conditions, but differed for the other condition. The five levels of COV were:

A) 1:9 – $\sigma^2_{11} = 1, \sigma^2_{21} = 1, \sigma^2_{12} = 1, \sigma^2_{22} = 1$;

B) 1:9 – $\sigma^2_{11} = 1, \sigma^2_{21} = 1, \sigma^2_{12} = 9, \sigma^2_{22} = 9$;

C) 9:1 – $\sigma^2_{11} = 9, \sigma^2_{21} = 9, \sigma^2_{12} = 1, \sigma^2_{22} = 1$;

D) H0 – $\sigma^2_{11} = 1, \sigma^2_{21} = 9, \sigma^2_{12} = 1, \sigma^2_{22} = 9$;

E) H1 – $\sigma^2_{11} = 1, \sigma^2_{21} = 9, \sigma^2_{12} = 9, \sigma^2_{22} = 1$.

In generating the data, two other "nuisance variables" were manipulated, due to their consistently large effects in other studies:

4) PROB: Probability of each of the subgroups in the population (p_1 and p_2). This was manipulated by varying the sizes ($n_1 = N*p_1$, $n_2 = N*p_2$) of the subgroups (2 levels)--Equal sized groups ($n_1=50$, $n_2=50$) or unequal group sizes ($n_1=90$, $n_2=10$).

5) DIST: Separation of subgroups. This was defined in terms of D_M, the Mahalanobis distance (in the populations) between the subgroup centroids:

$$D_M(12) = \sqrt{(\mu_1-\mu_2)'\Sigma^{-1}(\mu_1-\mu_2)} \qquad (12)$$

This distance was based on the pooled within-group covariance matrix: $\Sigma = p_1*\Sigma_1 + p_2*\Sigma_2$ DIST had 3 levels--$D_M = 2$, $D_M = 4$, or $D_M = 6$.

6) WEIGHT: The method of weighting the variables to form the similarity measure (6 levels)--which are discussed in a separate section below.

7) METHOD: The method of cluster analysis (11 levels)-- which are discussed in a separate section below.

The first five factors were fully crossed to yield 270 conditions. Twenty datasets were generated

for each condition according to the procedure given below, giving a total of 5400 base datasets. Although more replications would be desirable, the results of previous work (e.g., Donoghue, 1994b) indicate that this number of replications is likely to provide sufficient precision for the purposes of this study. Each dataset was then weighted according to each of the weighting methods, and analyzed by each of the hierarchical clustering methods, yielding a total of 356,400 cluster analyses. For each cluster analysis, the solution for the correct number of subgroups (i.e., G=2) was used as the result for that clustering method.

Data generation, variable weighting, and clustering were performed using FORTRAN programs written by the author. Eigenvalues and eigenvectors were computed using routines from EISPACK (Smith, Boyle, Garbow, Ikebe, Klema, & Moler, 1974). Accuracy of these programs was ensured through numerous comparisons of results of subroutines and final classifications with routines from SAS and SPLUS.

Data Generation

Subgroups were generated according to a finite mixture of normal distributions. All datasets consisted of 100 observations. The means were separated by both variables equally. To ensure that the data generation procedures worked properly, the Mahalanobis distance between the two known groups was computed for each dataset. Table 1 presents descriptive statistics for D_M.

Insert Table 1 about here

The means and medians for each of the conditions are very close to the desired values, supporting the validity of the data generation procedures.

Variable Weighting Methods

For analysis, each dataset was subjected to 6 variable weighting procedures. The procedures either yield a set of weights to apply to the variables before forming the Euclidean distance, or they yield

an alternative similarity measure such as D_M.

1) Euclidean distance (no weighting)

2) PC-R: Principal component scores based on R_T

3) Dm-T: D_M based on S_T

4) Ultrametric--d_E computed using weights from De Soete's (1986, 1988) algorithm to maximize agreement with the ultrametric inequality

5) ACE: D_M based on W^* from the ACE algorithm (Art, Gnanadesikan, & Kettenring, 1982). As in Art et al., the parameter m (the number of inter-entity distances used to determine the pairs used to estimate W^*) was set at two-thirds of the number of within-group pairs: $m = 1633$ for $p_1 = 0.5$ and $m = 2700$ for $p_1 = 0.9$.

6) Dm-W: D_M based on pooled within S_W.

A seventh method, principal component scores based on S_T, was originally included. However, because both component scores were retained, these scores are an orthogonal rotation of the original variables. Because the Euclidean distance is invariant under orthogonal rotation, *every one of the 59,400 solutions was identical to that computed from* d_E, and so these results were not included in the analyses discussed below. Clearly, clustering based on principal components is *not* the solution to the problem of within-group correlation.

The first and last methods provide useful comparisons for the other methods. Clearly, a weighting method which results in worse cluster recovery is undesirable. On the other hand, the last method provides a useful upper bound on how good recovery could be in a given dataset.

Cluster Algorithms

Each dataset was analyzed 11 times, corresponding to different hierarchical clustering algorithms. The clustering methods are:

1) Single linkage, distance

2) Complete linkage, distance

3) Ward's (1963) method, squared distance

4) EML-SAS's (1988) maximum likelihood hierarchical clustering procedure, which is a modification of Ward's method to alleviate the method's tendency to yield equal-sized clusters, squared distance.

5) Average flexible method, (Belbin, Faith, & Milligan, 1992), distance. Five levels of β were examined, 0.0, -.10, -.15, -.20, -.25. Note that $\beta = 0$ is the usual average linkage method.

6) Flexible-beta method (Lance & Williams, 1967), distance. Two levels of β were examined, -.25 and -.50.

The clustering methods were chosen because: a) they are widely used (single linkage, complete linkage, average linkage, and Ward's method); b) they have performed well in previous studies (average linkage, Ward's method, beta-flexible and flexible average); or c) they are designed to rectify a known weakness of another algorithm (EML). The values of β used are based on the studies by Milligan (1989a), Belbin, Faith, and Milligan (1992), and Donoghue, 1994b, 1995). For a discussion of these algorithms, the reader is referred to standard introductions to cluster analysis (e.g., Everitt, 1993; Lorr, 1983). Milligan (1989a), Belbin, Faith, and Milligan (1992), and Donoghue (1995) contain discussions of the beta-flexible and flexible average methods, and the SAS documentation (SAS Institute, 1988) is the primary reference for the EML algorithm.

Outcome Measure

The outcome measure for the study was the Hubert and Arabie (1985) modification of Rand's (1971) statistic, which will be denoted HA-Rand. The index was computed between each cluster solution

and the true subgroup membership used to generate the data. This index is based on examining pairs of entities, and determining whether they are classified into the same or different subgroups. A value of zero reflects chance agreement with the true membership, and 1.0 reflects perfect agreement. A study by Milligan and Cooper (1986) supports the accuracy of Hubert and Arabie's modification.

Analyses

To summarize the results, a factorial analysis of variance was conducted, as in Milligan (1980, 1981, 1989a) and Donoghue (1994b, 1995). The HA-Rand index served as the dependent variable. The independent variables were the design factors used to generate the data, weighting method, and the cluster algorithm used to analyze the data. The purpose of the ANOVA was to summarize the data and help to highlight the more important effects. Therefore, a measure of effect size was adopted in favor of traditional significance testing. Usually, η^2 would be used in this context:

$$\eta^2 = \frac{SS_{effect}}{SS_{Tot}} \quad . \tag{13}$$

However, this index has a disadvantage in large designs, namely that the denominator contains not only error variance and systematic variance of interest, but also irrelevant systematic variance due to other effects. The larger the design becomes, the more apparent this effect becomes. In the present case, this is particularly noisome, because one of the factors, Mahalanobis distance between the subgroup means, has a very large effect and so serves to obscure the effects of other factors. Therefore, an alternate version, η^2_{alt} (Tabachnick & Fidell, 1983, p. 47), was used:

$$\eta^2_{alt} = \frac{SS_{effect}}{SS_{effect} + SS_{error}} \quad . \tag{14}$$

Note that, unlike the other formulation, this version, η^2_{alt}, does not sum to 1.0. As in Donoghue (1994b), the practical criterion of $\eta^2_{alt} \geq .03$ was selected. Note that, given the large amount of data, any effect

which met the practical criterion was always highly significant (e.g., $p < .0001$).

Results

The results of the ANOVA and values of η^2_{ak} are summarized in Table 2. All of the main effects were identified as salient, with the exception of Prob. and R2, the correlation within subgroup 2. Means for the main effects are presented in Table 3. The main effects are all modified by salient interactions, and so will not be discussed in detail. However, a few comments are in order, bearing in mind that the observations may well be modified by the interactions. First, the extremely large effect of D, the distance between the subgroup centroids, is both noteworthy and expected; as the subgroups become more separated, the clustering task becomes easier and hence recovery improves. The smaller effect for R2 (compared to R1) is also an expected artifact of the design; for one-half of the datasets, subgroup 2 comprised only 10% of the sample, and so had a smaller effect. Finally, for the weighting methods, Table 3 reveals that, overall, best recovery is obtained for D_M-W, the Mahalanobis distance based on the pooled within-group covariance matrix. This is followed by distances based on the approximate covariance estimate, ACE; distances computed from the ultrametric weights; and PC-R, the principal components based on the total correlation matrix. Overall, D_M-T, Mahalanobis distance based on the total covariance matrix, yielded worse recovery than simply using the Euclidean distance d_E.

Insert Tables 2 and 3 about here

Weighting Method

The main effect of weighting method was modified by several salient interactions. Figure 1 portrays the R1 by Weight interaction. Three of the weighting methods, d_E, PC-R, and the ultrametric weights show large drops in recovery when R1 = -.7. The other three methods based on D_M (D_M-W,

ACE, and D_M-T) show a relatively flat profile; recovery using ACE actually decreases slightly as R1 increases. Although ultrametric weights and PC-R show lower recovery for R1=-.7, both methods yield good recovery for R1=0 and R1=.7, outperforming ACE.

Insert Figure 1 about here

Figure 2 plots the means of COV by Weight interaction. The effect appears to be due to the methods which are not based on Mahalanobis distance methods, d_E, PC-R and the ultrametric weights. The chief effect seems to be for H0, the condition in which $\sigma_{11}=\sigma_{21}=1$ and $\sigma_{12}=\sigma_{22}=3$. The ultrametric weights show a small decrease in recovery for this condition; PC-R has a substantial decrement in recovery, and d_E demonstrates a huge decrement in recovery. The three methods also differ to a lesser extent on H1, but give virtually identical results for the other conditions.

Insert Figure 2 about here

The Prob. by Weight interaction is portrayed in Figure 3. Dm-W is relatively unaffected by subgroup size. PC-R and ultrametric weights yield moderately lower recovery when $p_1 = .9$, and d_E yields substantially worse recovery. On the other hand, D_M-T and ACE yield better recovery for $p_1 = .9$ than for $p_1 = .5$. For ACE, the number of pairs used in the estimation, *m*, was larger for $p_1 = .9$, so this result may simply reflect more stable estimation from more data.

Insert Figure 3 about here

Finally, Figure 4 displays the means for the Weight by Method interaction. Although there are some differences, five of the weighting methods give very similar profiles of recovery across the clustering algorithms. On the other hand, D_M-T differs wildly in effectiveness. It performs well for Ward's method

and flexible average, but performs at or below the level of d_E when used with other methods. Because these two factors (clustering algorithm and weighting method) are under control of the analyst, this interaction is of considerable interest. Therefore, it will be examined in more detail below.

Insert Figure 4 about here

Clustering Methods

Three additional two-way interactions involving clustering method were identified as salient: Distance by Method, Prob. by Method, and COV by Method. Figure 5 portrays the means of the Distance by Method interaction. In general, the ordering of the methods is similar for each distance, although complete linkage ranks ahead of average linkage for $D_M = 2$, but behind average linkage when the groups are further apart. The largest difference is due to the single linkage method, which shows a very small gain (relative to other methods) from $D_M = 2$ to $D_M = 4$, and a consequent large relative gain from $D_M = 4$ to $D_M = 6$. Otherwise, the effects of increasing subgroup separation are relatively stable across the other methods.

Insert Figure 5 about here

Figure 6 plots the means for the Prob. by Method interaction. The clustering methods differ substantially in their recovery of equal- versus unequal-sized groups. Consistent with other studies (e.g., Donoghue, 1994b), single linkage yields much better recovery for unequal-sized groups, as do, to a lesser extent, EML and complete linkage. On the other hand, Ward's method yields much better recovery for equal-sized groups. EML and Ward's method showed a similar pattern in Donoghue (1994b), but there EML yielded slightly better recovery for equal-sized groups.

Insert Figure 6 about here

Finally, the COV by Method interaction is portrayed in Figure 7. The 1:1, H0 and H1 conditions present similar profiles of recovery across the clustering algorithms. The 1:9 condition results in much higher recovery for flexible average, beta-flexible and Ward's methods but lower recovery for average linkage. In general, the 9:1 condition yields a similar profile to the 1:9 condition, although the 1:9 condition results in worse recovery for single and average linkage. In spite of these differences, however, the clustering methods are, in general, similarly ordered for each condition of COV.

Insert Figure 7 about here

Other Effects

The two-way interaction of Distance by COV was identified as salient, as was the three-way interaction of Distance by Prob. by COV. Figures 8a and 8b plot the means of this three-way interaction. When $p_1 = .5$ as in Figure 8a, the Distance by COV interaction is fairly small. For each level of D_M, recovery is slightly lower for the H0 condition of COV than for the other conditions, although the amount does differ somewhat by D_M. However, when $p_1 = .9$ as in Figure 8b, there is a substantial interaction of Distance with COV. For $D_M = 2$, the 1:9 condition results in good recovery, while the recovery for the 9:1 condition falls near chance, and H0 and H1 yielded recovery equal to or better than that of the 1:1 condition. For $D_M = 4$, the 1:9 condition yields similar recovery to that of 1:1 and 9:1, and for $D_M = 6$, 1:9 results in somewhat lower recovery than the other two conditions.

Insert Figure 8 about here

Other Weight by Method Interactions

Inspection of Figure 4 indicated that the bulk of the Weight by Method interaction was due to the differing utility of D_M-T, the Mahalanobis distance between entities computed from Σ_T. Table 2 indicated that two three-way interactions involving Weight and Method (Distance by Weight by Method and Prob. by Weight by Method) were large but did not meet the criterion for salience. For completeness, plots of the means for these interactions are presented in the appendix. These interactions are largely due to the behavior of D_M-T; the interaction of D_M with Method increases with subgroup separation, and the interaction is much larger for $p_1 = .5$ than for $p_1 = .9$.

What Works Best

As was noted above, the Weight by Method interaction is of particular interest. While the other factors in the design are aspects of the data which are outside of the analyst's control, the weighting method and clustering algorithm are decisions made by the analyst. The key questions are:

1) Which weighting method yields the best recovery?

2) Which clustering algorithm yields the best recovery?

The salient interaction between Weight and Method indicates that the answer to either of these questions may depend on the value of the other factor. Essentially, we would like to know if the interaction is ordinal (effect size changes but the order of the levels of one factor remains stable across levels of the other) or disordinal (the ordering of results for one factor depends upon the level of the other factor).

Because these are explicitly ordinal questions, Cliff's (1993) distribution free method of comparing two distributions was used. Ordinal comparisons were performed using a modified version of Cliff's (1992) program PAIRDEL1, for paired observations. Two types of ordinal comparisons were made. The first estimates the probability that a randomly sampled observation from one distribution is higher (i.e., better recovery) than a randomly sampled observation from the other distribution. This results in one of

three decisions for each pair of methods: a) Method A is higher (better recovery) than Method B; b) Method B is higher than Method A; or c) the methods do not significantly differ. These pairwise comparisons were made on HA-Rand index recovery values. Shaffer's (1986) modification to the Bonferroni procedure was used to maintain familywise Type I error at $\alpha=0.05$. Finally, the pairwise relations were converted into ranks based upon the number of methods which were significantly higher than a given method versus the number which were significantly below it.

The second type of ordinal comparison is based on Cliff's index d_w, which is the proportion of datasets for which Method A yielded higher recovery than Method B minus the proportion of datasets for which Method B yielded higher recovery than Method A; d_w is the net proportion of datasets for which Method A yielded higher recovery. In the present context, it may be interpreted as the probability (for a randomly chosen dataset) of getting better recovery using Method A. Negative values of d_w indicate lower recovery for Method A.

Comparison of Weighting Methods

To determine which weighting methods work better, pairwise comparisons of the weighting methods were computed within each clustering algorithm, and ranks were formed based on the pairwise comparisons. For each clustering algorithm, the initial family size was 6 take 2 = 15. The results of these comparisons are summarized in Table 4.

Insert Table 4 about here

In spite of the strong interaction, the ranks of weighting methods are very consistent across clustering algorithms; only d_E and D_M-T show reversals across methods. Clustering using D_M-W (Mahalanobis distance based on the pooled within-groups covariance matrix) yielded best cluster recovery. Of the remaining methods, which do not require knowledge of the cluster structure, the ACE algorithm

(Art et al., 1982) is best, followed by the ultrametric weighting algorithm of De Soete (1986, 1988).

As was mentioned in the introduction, the (squared) Euclidean distance d_E is the default measure of similarity for most implementations of clustering procedures (e.g., statistical packages). Table 5 provides d_w values for each of the weighting methods compared to d_E. A negative value indicates that the method indexed at the top of the column gave superior recovery to that of d_E. For example, using d_E instead of ACE would yield lower recovery 8-24% (depending upon the clustering algorithm used) of the time when analyzing datasets similar to those used here. Table 5 also gives d_w values for each of the remaining methods compared to the best method, ACE. In comparing the two best methods which do not require knowledge of the subgroup structure, ACE and ultrametric, the d_w value varies somewhat by clustering algorithm, but is always greater than 0; for the type of data considered in this study, ACE provides better recovery than ultrametric weights.

Insert Table 5 about here

The last two columns of Table 5 compare cluster recovery using the two best weighting methods (ACE and ultrametric weights) to cluster recovery using D_M-W. Thus, knowing the subgroup structure and clustering based on D_M-W instead of ACE would result in improved recovery 10-18% of the time, unless the analyst used the single linkage algorithm.

Comparison of Clustering Algorithms

A similar procedure was used to rank the clustering algorithms. Within each weight method, all pairwise ordinal comparisons of clustering methods were performed and the pairwise relations were converted into ranks. Shaffer's modification to the Bonferroni was again used, with the initial family size of 11 take 2 = 55. The results of these analyses are summarized in Table 6.

Insert Table 6 about here

The ranks of the clustering methods are more variable than those of the weights. However, the flexible average method of Belbin, Faith, and Milligan (1992) clearly outperforms the other algorithms. For the conditions examined in this study, $\beta = -.15$ or $\beta = -.20$ gave the best recovery. These values coincide with Belbin et al.'s recommendation that $\beta \geq -.2$, although they are slightly lower than the final value they suggest, $\beta = -.10$. However, for the best weighting conditions, $\beta = -.10$ yielded very similar results to the best values.

Although there are some minor differences, the results for the remaining methods are similar to those obtained in other studies (e.g., Donoghue, 1994a,b; Milligan 1989a,b; Belbin, Faith, & Milligan, 1992). The results for the lowest of the methods, complete linkage and single linkage, are quite consistent. Based on theoretical considerations, such as its relationship to the minimum spanning tree of graph theory, some authors continue to recommend single linkage (e.g., IMS Panel on Discrimination, Classification, and Clustering, 1989). Yet this method uniformly produced the lowest recovery of the methods examined, a result that is routinely found in comparisons clustering algorithms (e.g., Milligan & Cooper, 1987, and the references therein).

Table 7 presents d_w values for comparing each clustering method to one of the best (although not widely available) clustering methods, flexible average with $\beta = -.15$, and comparing each clustering method to one of the best of the widely available algorithms, Ward's method. In the present study, using the flexible average method instead of single linkage gives $d_w = .441$ for d_E, .590 for ACE, and .524 for ultrametric weights. Using single linkage gives worse recovery about *one-half of the time!* Even compared to Ward's method, which is very widely available, d_w is over .30 for all weighting methods.

Insert Table 7 about here

Limitations and Future Work

The following is a very brief discussion of some related areas for future research. It is not intended to be exhaustive by any means. In order to keep this section reasonably brief, procedures which differ from the present paper's focus on distance-based measures are not discussed. Examples of other approaches not considered here include non-distance similarity coefficients (e.g., q-correlations) and algorithms which combine specific variable weighting or multidimensional scaling models with specific clustering algorithms.

While restricting the present investigation to bivariate data somewhat limits its generalizability, it was felt that this provides minimal test of the weighting procedures; any procedure which does not function well with bivariate data seems unlikely to be useful for higher dimensional cases. Having established here that variable weighting methods can provide substantial benefit in cluster recovery, further work is needed to determine the extent to which the results obtained here generalize to higher numbers of subgroups and higher dimensional clustering problems.

Certain aspects of the methods used, such as how to choose the number of distances m to use in computing the ACE estimate of Σ, need to be addressed. Currently, there is little to guide the applied researcher. J. Kettenring (personal communication, July 2, 1993) indicates that some work along these lines is underway at Bellcore. Obviously, more work would be useful. A related issue is the relationship of the original formulation of the method, used here, to the somewhat modified version which is implemented in SAS's PROC ACECLUS (1988).

The relationship between the methods used here and procedures aimed at variable standardization

(Milligan & Cooper, 1988; Barton, 1993) should be examined. Variable standardization methods seek to deal with problems associated with combining variables measured on very different scales (such as SAT and GPA) into a single similarity coefficient. Hence, variable standardization procedures tend to treat variables sequentially, as opposed to the multivariate focus of the procedures examined in the present study.

Of the clustering methods examined in this study, the flexible average clustering method (Belbin, Faith, & Milligan, 1992) gave the best recovery of the methods in this study. The optimal value of β was found to be -.15 to -.20, which is slightly lower than the value of $\beta = -.10$ suggested by Belbin et al. (1992). A companion paper (Donoghue, 1995) presents further results comparing the flexible average and beta-flexible methods. Of the remaining methods, Ward's method and beta-flexible linkage ($\beta = -.50$) yielded the best recovery, followed closely by SAS's EML algorithm.

The relationship of the weighting methods identified here to the closely allied problem of variable selection (Milligan, 1989b; Donoghue, 1994a) remains to be addressed. Both of these papers found that the ultrametric weights were useful in ameliorating the degradation of cluster recovery caused by including irrelevant variables in the cluster analysis. Donoghue (1994a) also compared two additional variable selection procedures, and in their original paper, Art et al. (1982) presented preliminary evidence that the ACE weighting method may be useful with the variable selection problem. More work is needed to understand the interrelationship of the various variable weighting techniques proposed to solve different problems in clustering.

Conclusion

This study was meant to constitute a first step in understanding the utility of various variable weighting algorithms. The results of Donoghue (1994b) clearly indicate that cluster analyses based upon

the Euclidean distance can yield suboptimal results in the presence of within-group correlation, but could not offer clear suggestions for alternatives.

Variable weighting methods were found to have a large effect on cluster recovery. Of the methods which do not require a priori knowledge of the subgroup structure, the ACE method of Art, Gnanadesikan, and Kettenring (1982) yielded the best results. When used with the better clustering algorithms, this method provided a net improvement in 17% (EML) to 24% (beta-flexible, $\beta = -.50$) of the datasets examined. When used with the same clustering methods, the next best weighting method, ultrametric weights, yielded improved recovery 16-21% of the time. However, ultrametric weighting was found to be more sensitive than ACE to within-subgroup correlation. Therefore, ACE is the method which is preferred overall. There is still plenty of room for improvement, however. Comparisons of ACE with D_M based on the pooled within-group covariance matrix indicated that knowing the correct covariance matrix would yield improved recovery (over ACE) approximately 10% of the time.

Finally, it should be noted that the procedures examined and the results obtained here only apply to situations in which a mixture model formulation of the clustering problem makes sense. In some educational applications, such as clustering test items based on multidimensional IRT parameters (Miller & Hirsch, 1992), it is far from obvious whether the mixture model formulation of the clustering problem is valid. The application of the present work to such situations is problematic.

This study is intended to be a first step in understanding variable weighting methods. It attempts to provide some information to those educational investigators faced with doing empirical cluster analyses, allowing them to make a better informed choice of variable weighting methods and clustering algorithms.

References

Art, D., Gnanadesikan, R., & Kettenring, J. R. (1982). Data-based metrics for cluster analysis. Utilitas Mathematica, 21A, 75-99.

Barton, R. M. (1993, April). Standardizing variables in cluster analysis. Paper presented at the annual meeting of the American Educational Research Association, Atlanta, GA.

Belbin, L., Faith, D. P., & Milligan, G. W. (1992). A comparison of two approaches to beta-flexible clustering. Multivariate Behavioral Research, 27, 417-433.

Blashfield, R. K. (1976). Mixture model tests of cluster analysis: Accuracy of four agglomerative hierarchical methods. Psychological Bulletin, 83, 377-388.

Chang, W-C. (1983). On using principal components before separating a mixture of two multivariate normal distributions. Applied Statistics, 32, 267-275.

Cliff N. (1992). PAIRDEL1.BAS: Program for computing matched-data d-statistics [computer program]. Los Angeles: Psychology Department, University of Southern California.

Cliff, N. (1993). Dominance relations: Ordinal analyses to answer ordinal questions. Psychological Bulletin, 114, 494-509.

De Soete, G. (1986). Optimal variable weighting for ultrametric and additive tree clustering. Quality and Quantity, 20, 169-180.

De Soete, G. (1988). Software abstract - OVWTRE: A program for optimal variable weighting for ultrametric and additive tree fitting. Journal of Classification, 5, 101-104.

Donoghue, J. R. (1994a). Variable screening for cluster analysis. Research Report No. RR-94-36. Princeton, NJ: Educational Testing Service.

Donoghue, J. R. (1994b). A preliminary study of the effects of within-group covariance structure on recovery in cluster analysis. Research Report No. RR-94-46. Princeton, NJ: Educational Testing Service.

Donoghue, J. R. (1995). A comparison of beta-flexible and flexible average clustering methods in the presence of a variety of within-group covariance structures. Under review, Research Report Series. Princeton, NJ: Educational Testing Service.

Everitt, B. S. (1993). Cluster analysis (3rd Ed.). New York: John Wiley & Sons.

Hartigan, J. A. (1975). Clustering algorithms. New York: John Wiley & Sons.

Hubert, L., & Arabie, P. (1985). Comparing partitions. Journal of Classification, 2, 193-218.

IMS Panel on Discriminant Analysis, Classification, and Clustering (1989). Discriminant analysis and clustering. Statistic Science, 4, 34-69.

Johnson, S. C. (1967). Hierarchical clustering schemes. Psychometrika, 32, 47-62.

Lance, G. N., & Williams, W. T. (1967). A general theory of classificatory sorting strategies: 1. Hierarchical systems. Computer Journal, 9, 373-380.

Lorr, M. (1983). Cluster analysis for social scientists. San Francisco: Jossey-Bass Publishers.

McLachlan, G. J., & Basford, K. E. (1988). Mixture models: Inference and applications to clustering. New York: Marcel Dekker.

Miller, T. R., & Hirsch, T. M. (1992). Cluster analysis of angular data in applications of multidimensional item-response theory. Applied Measurement in Education, 5, 193-211.

Milligan, G. W. (1979). Ultrametric hierarchical clustering algorithms. Psychometrika, 44, 343-346.

Milligan, G. W. (1980). An examination of the effects of six types of error perturbation on fifteen clustering algorithms. Psychometrika, 45, 325-342.

Milligan, G. W. (1981). A Monte Carlo study of thirty internal criterion measures for cluster analysis. Psychometrika, 46, 187-199.

Milligan, G. W. (1989a). A study of the beta-flexible clustering method. Multivariate Behavioral Research, 24, 163-176.

Milligan, G. W. (1989b). A validation study of variable weighting algorithm for cluster analysis. Journal of Classification, 6, 53-71.

Milligan, G. W., & Cooper, M. C. (1985). An examination of procedures for determining the number of clusters in a data set. Psychometrika, 50, 159-170.

Milligan, G. W., & Cooper, M. C. (1986). A study of comparability of external criteria for hierarchical cluster analysis. Multivariate Behavioral Research, 21, 441-458.

Milligan, G. W., & Cooper, M. C. (1987). Methodology review: Clustering methods. Applied Psychological Measurement, 11, 329-354.

Milligan, G. W., & Cooper, M. C. (1988). A study of variable standardization. Journal of Classification, 5, 181-204.

Milligan, G. W., & Isaac, P. D. (1980). The validation of four ultrametric clustering algorithms. Pattern Recognition, 12, 41-50.

Rand, W. M. (1971). Objective criteria for the evaluation of clustering methods. Journal of the American Statistical Association, 66, 846-850.

Rohlf, F. J. (1970). Adaptive hierarchical clustering schemes. Systematic Zoology, 19, 58–82.

SAS Institute, Inc. (1988). SAS/STAT user's guide: Release 6.03 edition. Cary, NC: Author.

Scheibler, W., & Schneider, D. (1985). Monte Carlo tests of the accuracy of cluster analysis algorithms: A comparison of hierarchical and nonhierarchical methods. Multivariate Behavioral Research, 20, 283-304.

Shaffer, J. P. (1986). Modified sequentially rejective multiple test procedures. Journal of the American Statistical Association, 81, 826-831.

Smith, B. T., Boyle, J. M., Garbow, B. S., Ikebe, Y., Klema, V. C., & Moler, C. B. (1974). Matrix eigensystem routines: EISPACK guide. New York: Springer-Verlag.

Tabachnick, B. G., & Fidell, L. S. (1983). Using multivariate statistics. New York: Harper and Row.

Titterington, D. M., Smith, A. F. M., & Makov, U. E. (1985). Statistical analysis of finite mixture distributions. New York: John Wiley & Sons.

Ward, J. H. (1963). Hierarchical grouping to optimize an objective function. Journal of the American Statistical Association, 58, 236-244.

Table 1
Descriptive Statistics for Observed D_M

D_M	Mean	Std.	Min.	Q_1	Med.	Q_3	Max.
2	2.086	0.454	0.372	1.835	2.051	2.300	4.611
4	4.106	0.558	2.127	3.775	4.063	4.357	7.185
6	6.143	0.730	3.511	5.691	6.067	6.500	10.690

Table 2
Main Effects and Salient Interactions ($\eta^2_{ak} \geq .03$) for ANOVA of HA-Rand Index

EFFECT	DF	SS	η^2_{ak}
D	2.	23826.77	.641
P	1.	59.61	.004
C	4.	648.85	.046
R1	2.	425.51	.031
R2	2.	97.03	.007
M	10.	4166.77	.238
W	5.	1452.93	.098
D*C	10.	540.93	.039
D*M	20.	702.38	.050
P*M	10.	723.06	.051
C*M	40.	436.27	.032
C*R1	8.	337.65	.025
D*W	10.	332.11	.024
P*W	5.	671.72	.048
C*W	20.	834.55	.059
R1*W	10.	568.05	.041
R2*W	10.	83.78	.006
M*W	50.	631.73	.045
D*P*C	8.	414.63	.030
D*M*W	100.	328.51	.024
P*M*W	50.	312.40	.023
Error	338580.	13353.61	—

Abbreviations: D - Mahalanobis distance between subgroup centroids, P - probability of subgroup membership, C - covariance matrix condition, R1 - correlation in larger group (when $p_1 \neq p_2$), R2 - correlation in smaller group (when $p_1 \neq p_2$), M - method of clustering, W - weighting method.

Table 3
HA-Rand Index Means and (Std. Dev.) for Selected Effects

D_M			Prob.	
2	4	6	$p_1 = 0.5$	$p_1 = 0.9$
.241 (.249)	.637 (.362)	.867 (.283)	.595 (.396)	.569 (.399)

COV				
1:1	1:9	9:1	H0	H1
.594 (.405)	.636 (.354)	.584 (.441)	.505 (.410)	.590 (.395)

R1			R2		
-.7	0.0	0.7	-.7	0.0	0.7
.533 (.411)	.607 (.389)	.606 (.387)	.559 (.408)	.591 (.394)	.596 (.389)

Weight					
Euclid	Dm-T	Dm-W	PC-R	ACE	Ultrametric
.512 (.418)	.492 (.400)	.677 (.352)	.583 (.402)	.627 (.381)	.599 (.397)

Method	Mean Recovery
Single Link (Si)	.318 (.414)
Complete Link (Cm)	.456 (.390)
Ward's Method (Wa)	.623 (.385)
EML	.609 (.389)
Average Linkage (Avg.)	.515 (.422)
Flexible Average, β = -.10 (Av10)	.663 (.365)
Flexible Average, β = -.15 (Av15)	.682 (.353)
Flexible Average, β = -.20 (Av20)	.682 (.353)
Flexible Average, β = -.25 (Av25)	.673 (.359)
Beta Flexible, β = -.25 (Fx25)	.568 (.388)
Beta Flexible, β = -.50 (Fx50)	.609 (.381)

Table 4
Ranks of Weighting Methods Based on Ordinal Comparisons
(by Clustering Method)

Weighting Method	Si	Cm	Wa	EML	Avg.	Av10	Av15	Av20	Av25	Fx25	Fx50
Dm-W	1.5[a]	1	1	1	1	1	1	1	1	1	1
ACE	1.5[a]	2	2	2	2	2.5[b]	2	2	2	2	2
Ultrametric	3	3	3	3	3	2.5[b]	3	3	3	3	3
PC-R	4	4	4	4	4	4	4	4.5[c]	4.5[d]	4	4
Dm-T	6	6	5	6	6	5	5	4.5[c]	4.5[d]	6	5.5[e]
Euclid	5	5	6	5	5	6	6	6	6	5	5.5[e]

[abcde] Entries with common superscripts do not significantly differ from one another.

Table 5
d_w Values for Selected Comparisons of Weighting Methods
(by Clustering Method)

	Euclid					ACE			Dm-W	
	Dm-T	PC-R	Ultra.	ACE	Dm-W	Dm-T	PC-R	Ultra.	ACE	Ultra.
Si	.085	-.031	-.053	-.081	-.069	.169	.050	.026	-.007*	.017
Cm	.275	-.121	-.182	-.234	-.417	.486	.123	.053	.184	.251
Wa	-.070	-.133	-.168	-.230	-.331	.166	.104	.067	.112	.176
EML	.165	-.147	-.160	-.168	-.272	.342	.046	.025	.109	.134
Avg.	.213	-.097	-.120	-.132	-.224	.350	.043	.010*	.096	.109
Av10	-.034	-.148	-.162	-.160	-.280	.140	.025	.016*	.128	.135
Av15	-.113	-.160	-.163	-.184	-.296	.086	.048	.033	.130	.160
Av20	-.127	-.155	-.176	-.210	-.306	.091	.069	.052	.116	.165
Av25	-.121	-.139	-.171	-.222	-.303	.104	.086	.061	.103	.155
Fx25	.114	-.154	-.211	-.239	-.393	.348	.114	.066	.161	.214
Fx50	-.010*	-.144	-.174	-.244	-.366	.246	.119	.072	.118	.199

* Does not significantly differ from 0.0, p = .05.

Table 6
Ranks of Clustering Algorithms Based on Ordinal Comparisons
(by Weighting Method)

	Euclid	Dm-T	Dm-W	PC-R	ACE	Ultrametric
Av20	2^{ab}	1.5^{f}	1^{h}	2	1^{n}	1.5^{r}
Av15	1^{a}	1.5^{f}	2^{hi}	1	3^{o}	1.5^{r}
Av10	3^{bc}	4	4	3.5^{l}	5^{p}	4^{s}
Av25	4^{c}	3	3^{i}	3.5^{l}	2^{no}	3^{s}
Wa	6^{de}	5	5.5^{j}	6.5^{m}	5^{p}	6^{t}
Fx50	7^{e}	6	5.5^{j}	6.5^{m}	5^{p}	6^{t}
EML	5^{d}	7	7.5^{k}	5	7	6^{t}
Fx25	8	8	7.5^{k}	8	8	8
Avg.	9	9.5^{g}	10	9	9.5^{q}	9
Cm	10	9.5^{g}	9	10	9.5^{q}	10
Si	11	11	11	11	11	11

39

^{abcdefghijklmnopqrst} Entries with common superscripts do not significantly differ from one another.

40

Table 7
d_u Values for Selected Comparisons of Clustering Methods
(by Weighting Method)

	Si	Cm	Wa	EML	Avg.	Av10	Av15	Av20	Av25	Fx25	Fx50
Comparison with Flexible Average, $\beta = -.15$											
Euclid	.440	.394	.142	.131	.247	.030	----	.009*	.025	.221	.137
Dm-T	.723	.689	.159	.385	.566	.107	----	-.006*	.017*	.442	.259
Dm-W	.613	.295	.088	.118	.274	.034	----	-.005*	.011*	.131	.079
PC-R	.536	.411	.136	.123	.273	.035	----	.016	.034	.216	.150
ACE	.591	.326	.076	.116	.296	.055	----	-.018	-.010*	.142	.069
Ultrametric	.521	.359	.114	.114	.262	.021	----	-.003*	.010*	.180	.116
Comparison with Ward's Method											
Euclid	.319	.270	----	.005*	.122	-.109	-.142	-.126	-.110	.086	-.005*
Dm-T	.543	.546	----	.251	.431	-.044	-.159	-.173	-.148	.285	.077
Dm-W	.545	.212	----	.026	.200	-.054	-.088	-.087	-.065	.028	-.012*
PC-R	.386	.273	----	-.008*	.143	-.102	-.136	-.124	-.104	.071	-.010*
ACE	.541	.274	----	.058	.246	-.011*	-.076	-.096	-.095	.076	-.015*
Ultrametric	.416	.259	----	.008*	.158	-.087	-.114	-.116	-.110	.059	-.005*

* Does not significantly differ from 0.0, $p = .05$.

Figure Captions

Figure 1. Plot of mean cluster recovery (HA-Rand) for two-way interaction of correlation in the larger group (R1) with variable weighting method (Weight).

Figure 2. Plot of mean cluster recovery (HA-Rand) for two-way interaction of covariance condition (COV) with variable weighting method (Weight).

Figure 3. Plot of mean cluster recovery (HA-Rand) for two-way interaction of subgroup size (probability of subgroup 1 membership--p_1) with variable weighting method (Weight).

Figure 4. Plot of mean cluster recovery (HA-Rand) for two-way interaction of variable weighting method (Weight) with clustering method (Method).

Figure 5. Plot of mean cluster recovery (HA-Rand) for two-way interaction of Mahalanobis distance between the centroids of the subgroups (Distance) with clustering method (Method).

Figure 6. Plot of mean cluster recovery (HA-Rand) for two-way interaction of subgroup size (probability of subgroup 1 membership--p_1) with clustering method (Method).

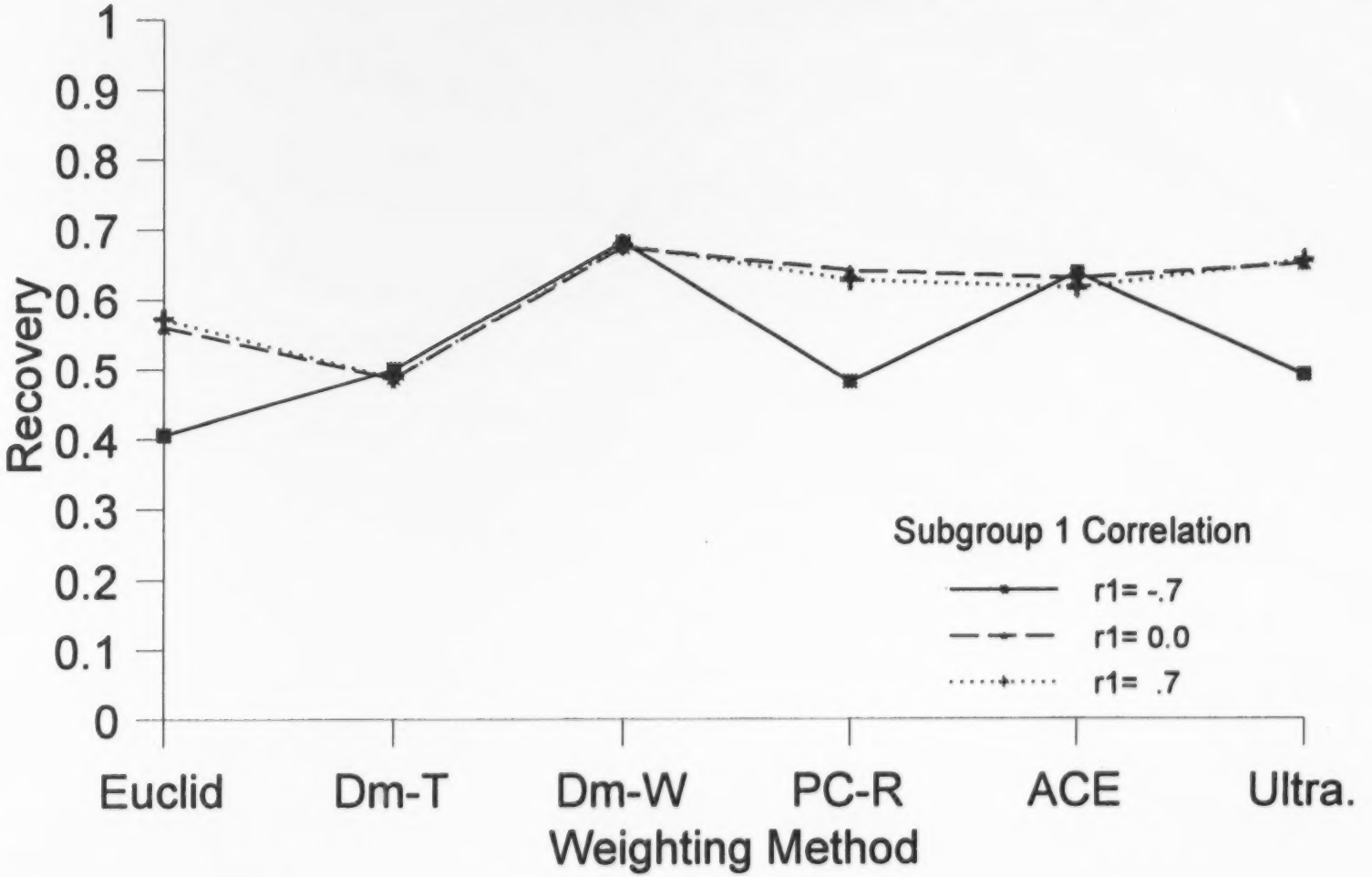
Figure 7. Plot of mean cluster recovery (HA-Rand) for two-way interaction of covariance condition (COV) with clustering method (Method).

Figure 8. Plot of mean cluster recovery (HA-Rand) for three-way interaction of Mahalanobis distance between the centroids of the subgroups (Distance) with covariance condition (COV) with subgroup size (probability of subgroup 1 membership--p_1).

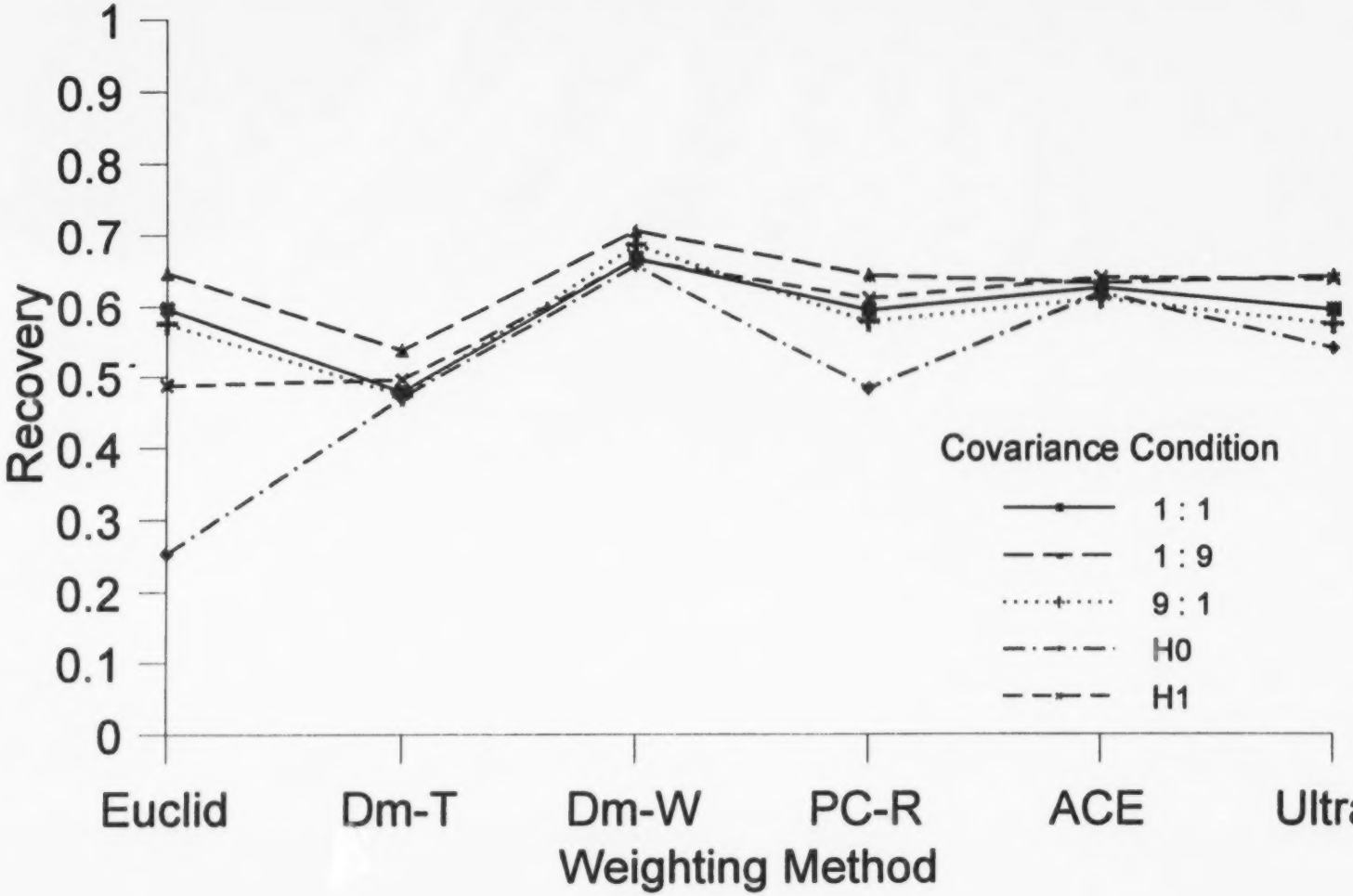
a) Distance by COV interaction for equal-sized groups ($p_1 = .5$).

b) Distance by COV interaction for unequal-sized groups ($p_1 = .9$).

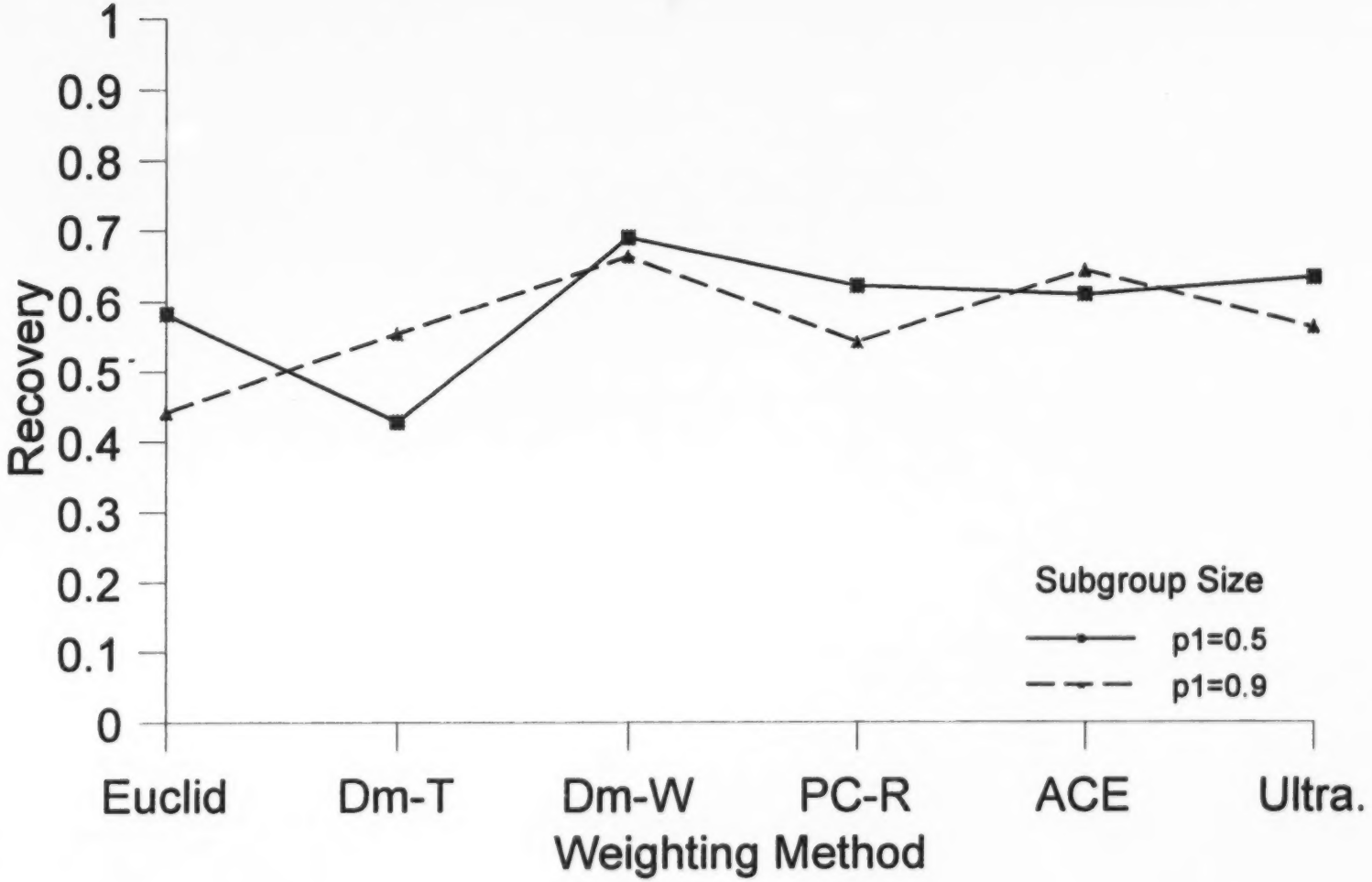
R1 by Weight Interaction



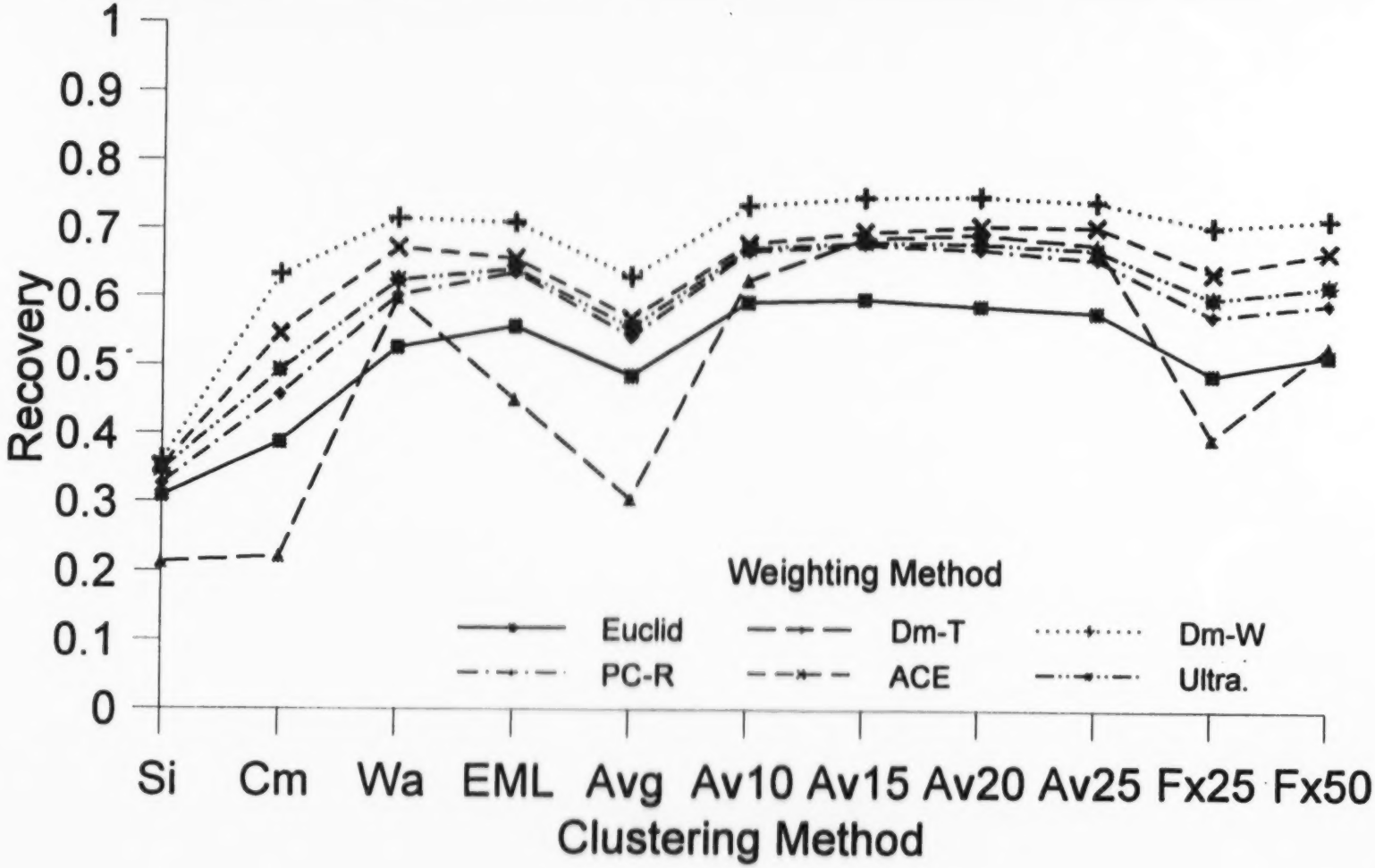
COV by Weight Interaction



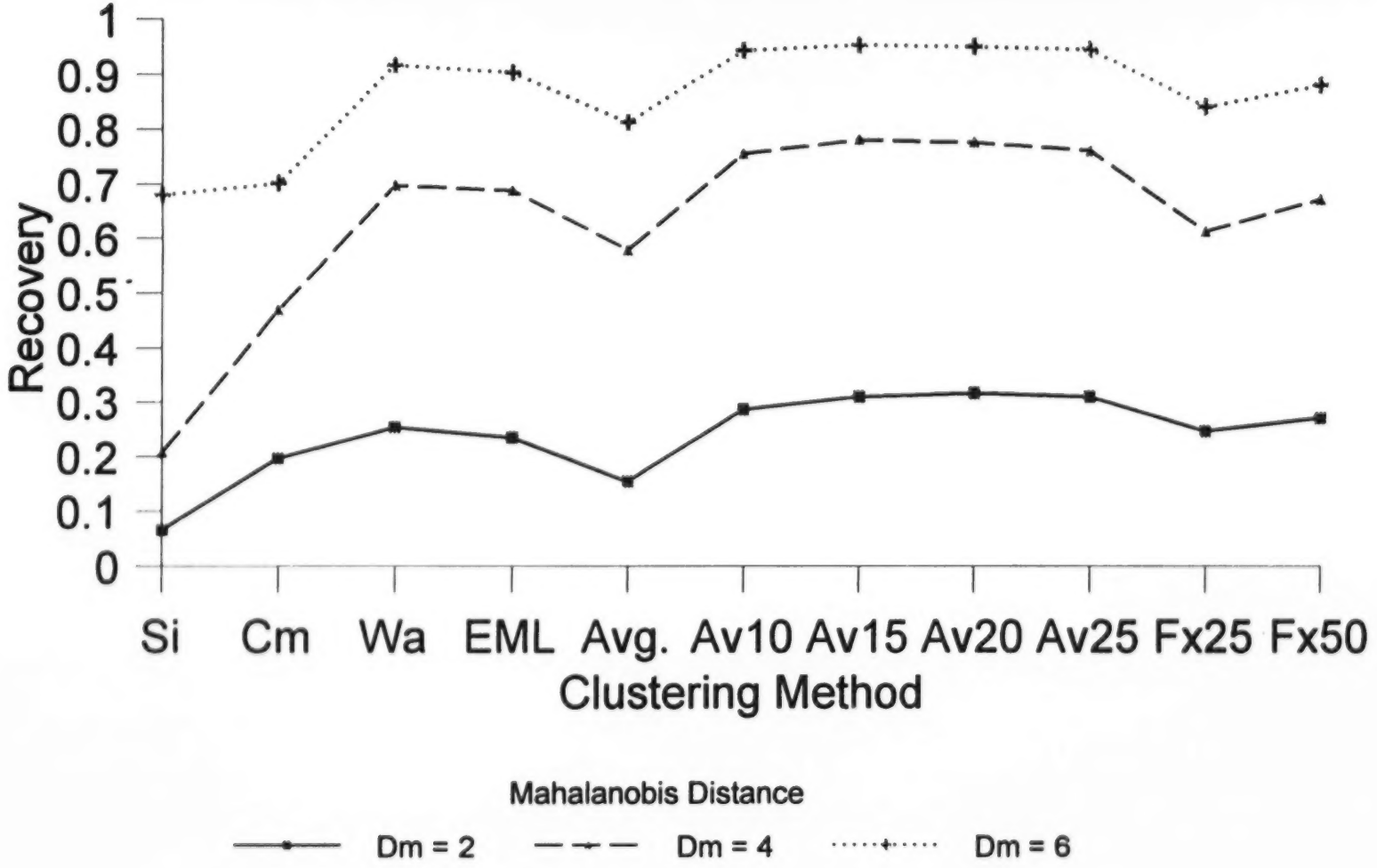
Prob. by Weight Interaction



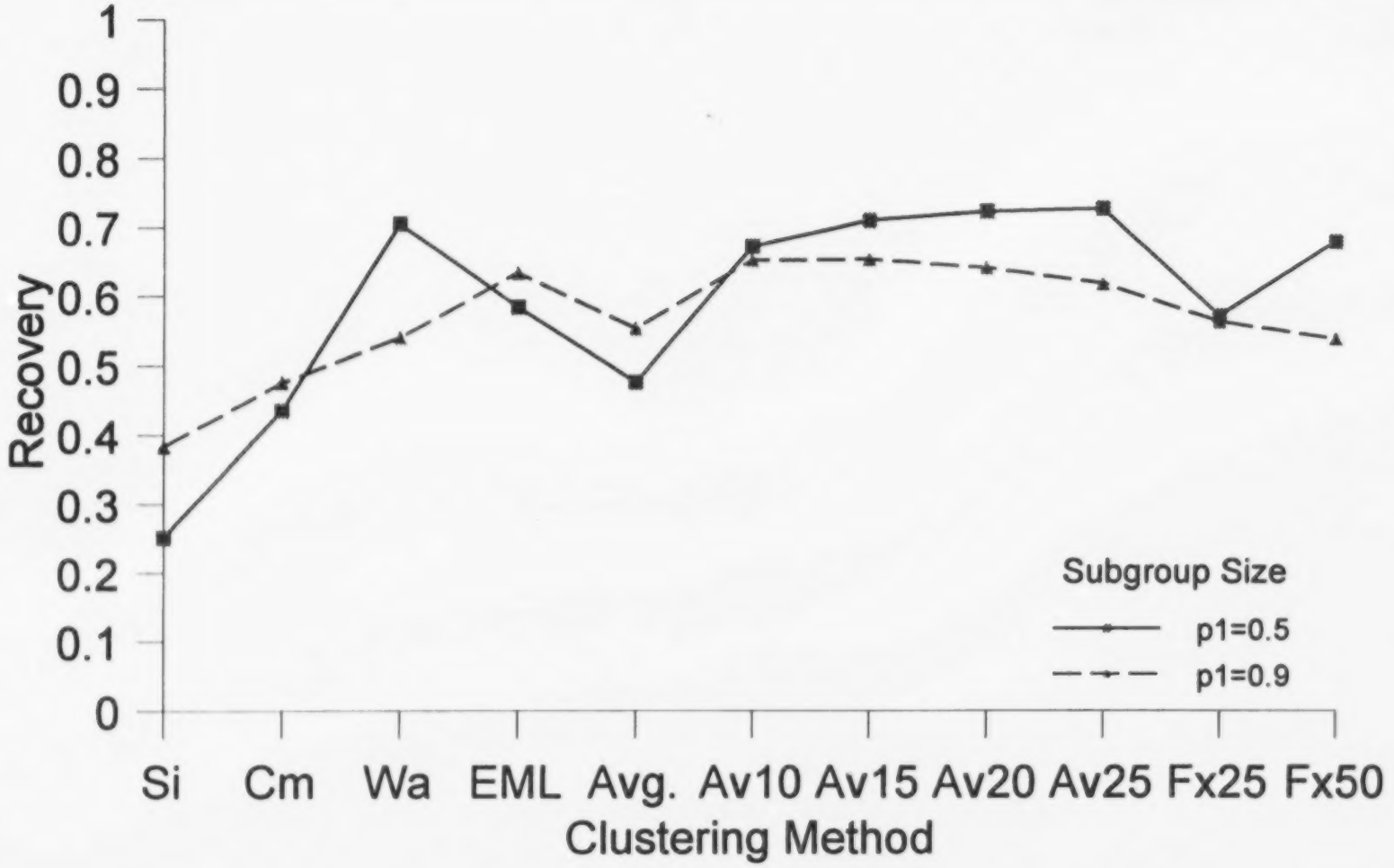
Weight by Method Interaction



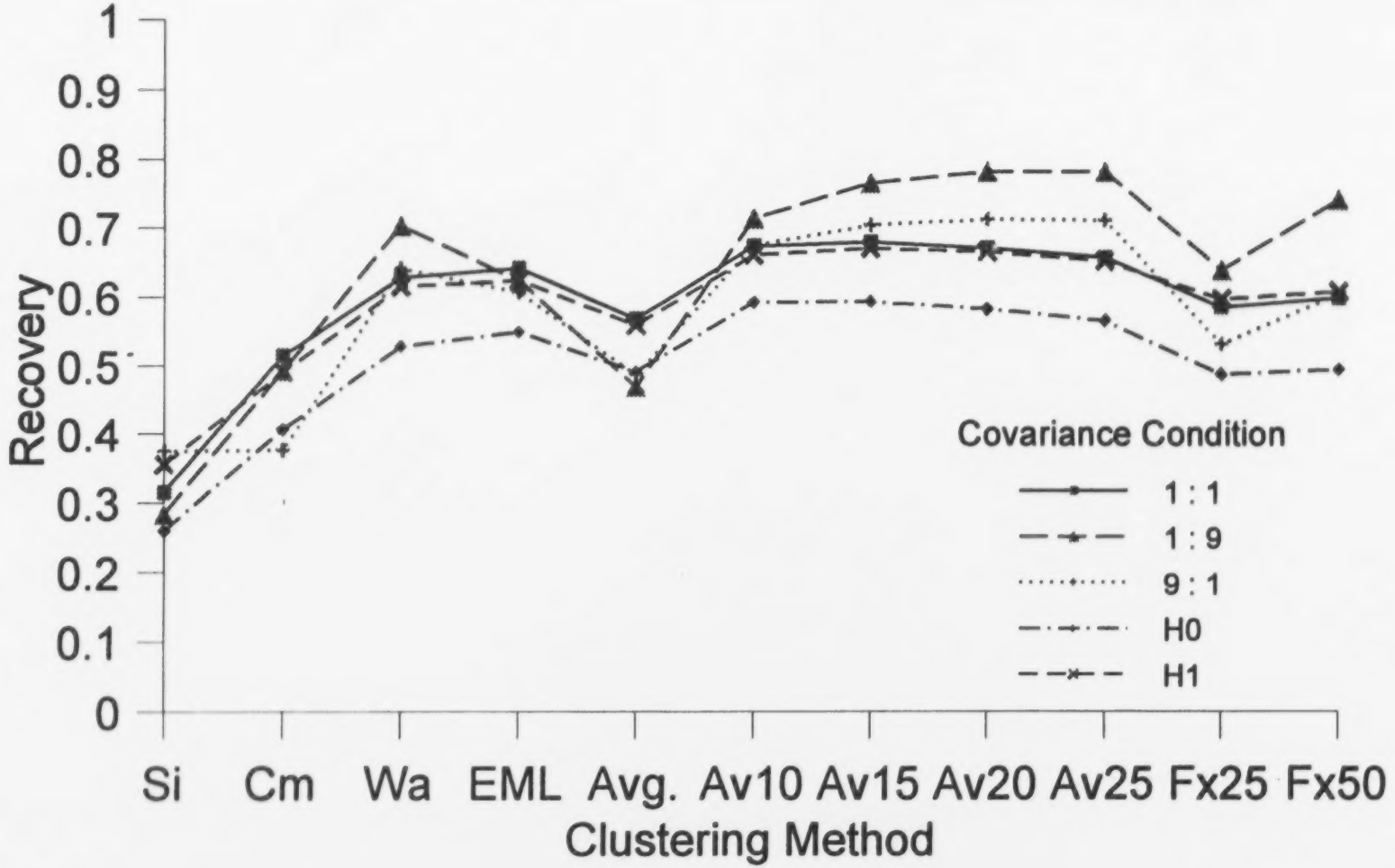
Dist. by Method Interaction



Prob. by Method Interaction

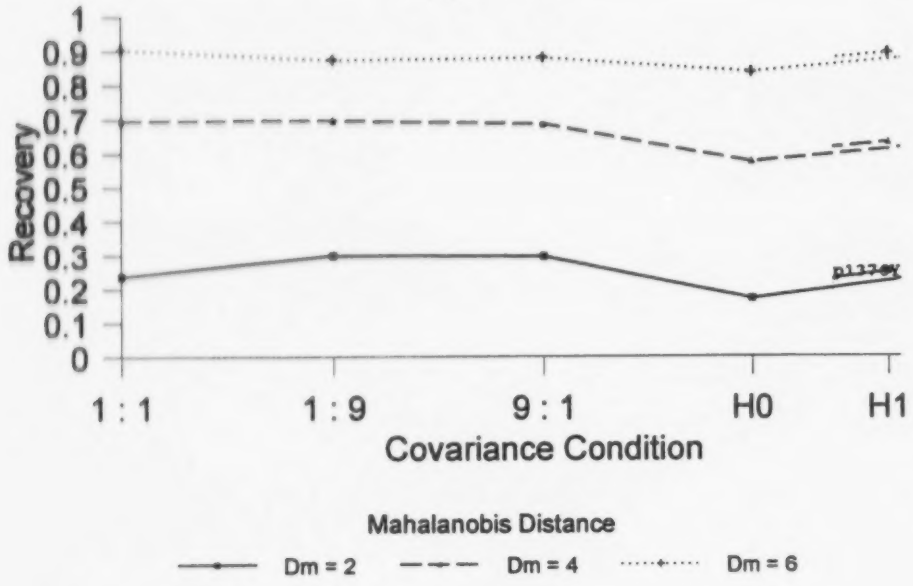


COV by Method Interaction



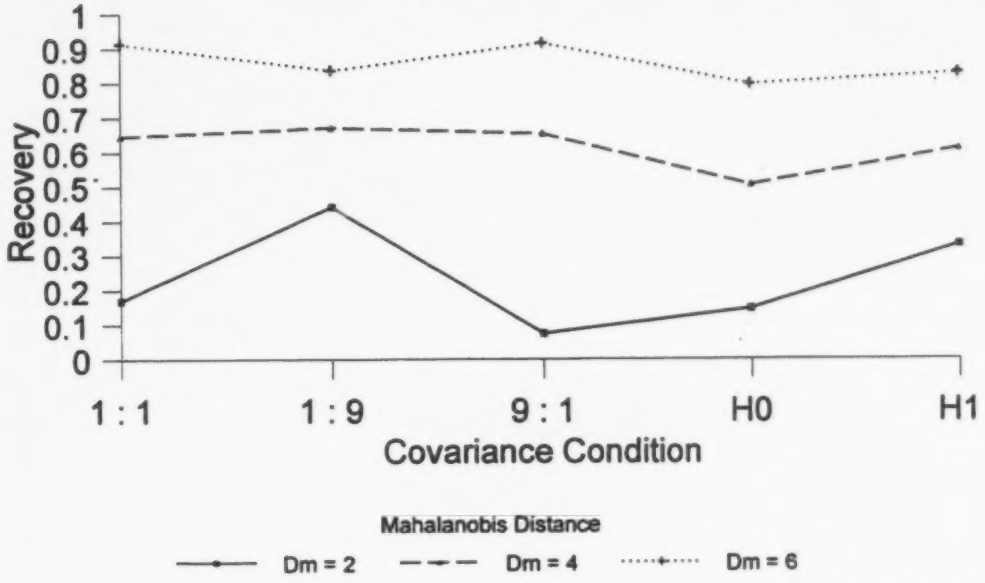
Dist. by COV Interaction

a) p1 = 0.5



Dist. by COV Interaction

b) p1 = 0.9



Appendix

Additional Figures

Captions for Additional Figures

Figure A1. Plot of mean cluster recovery (HA-Rand) for three-way interaction of Mahalanobis distance between the centroids of the subgroups (Distance) with variable weighting method (Weight) with clustering method (Method).

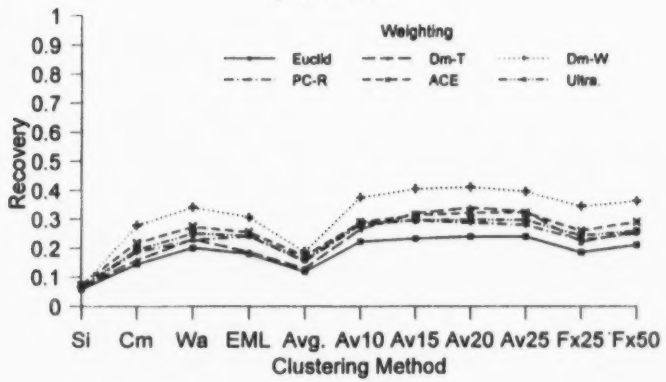
a) Weight by Method interaction for $D_M = 2.0$.
b) Weight by Method interaction for $D_M = 4.0$.
c) Weight by Method interaction for $D_M = 6.0$.

Figure A2. Plot of mean cluster recovery (HA-Rand) for three-way interaction of subgroup size (probability of subgroup 1 membership--p1) with variable weighting method (Weight) with clustering method (Method).

a) Weight by Method interaction for equal-sized groups ($p_1 = .5$).
b) Weight by Method interaction for unequal-sized groups ($p_1 = .9$).

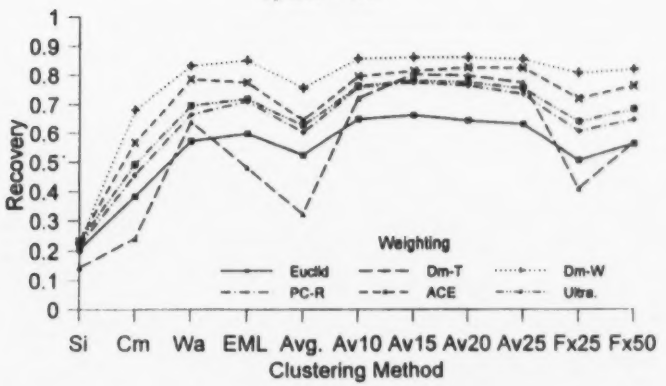
Weight by Method Interaction

a) Dm = 2.0



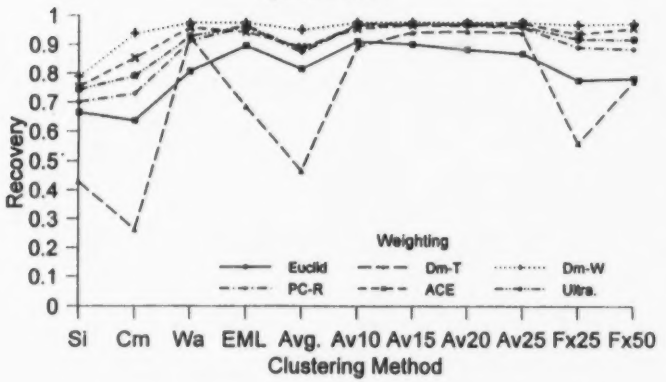
Weight by Method Interaction

b) Dm = 4.0



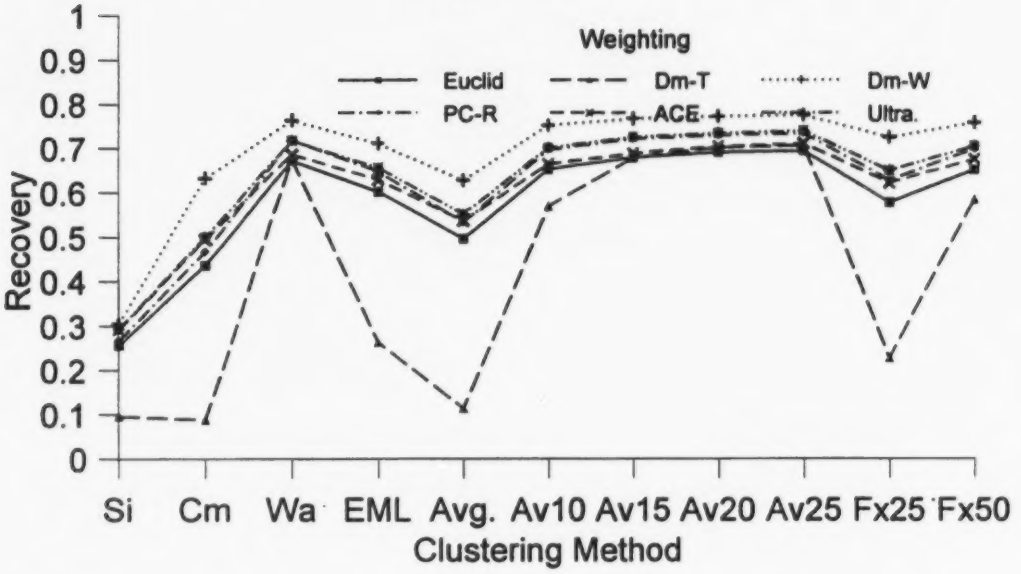
Weight by Method Interaction

c) Dm = 6.0



Weight by Method Interaction

a) p1 = 0.5



Weight by Method Interaction

b) p1 = 0.9